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Optimising Laboratory Workflows with Low-Code /No-Code Software Solutions

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Abstract— Modern laboratories increasingly depend on heterogeneous instruments, digital records, and data-processing applications that often operate as disconnected workflow components. Low-code/no-code (LCNC) platforms provide an emerging approach for integrating these components while reducing dependence on specialised software-development expertise. This study investigates whether configurable LCNC workflow orchestration can improve laboratory efficiency while preserving reproducibility, traceability, data integrity, and adaptability. A research framework is proposed in which routine laboratory operations are represented as event-driven workflow modules incorporating sample registration, task allocation, validation, instrument-data ingestion, exception handling, and report generation. The central research gap concerns the limited empirical assessment of LCNC solutions across multiple laboratory performance dimensions rather than execution time alone. The proposed study therefore compares conventional semi-manual workflow management with an LCNC-enabled laboratory workflow using operational, quality, interoperability, and usability indicators. Particular emphasis is placed on workflow configuration by laboratory personnel, automated validation rules, auditability, API-based data exchange, and reduction of repetitive administrative intervention.

Keywords— Low-Code/No-Code, Laboratory Automation, Workflow Optimisation, Laboratory Informatics, Digital Health, Process Automation

Introduction

Laboratory environments have undergone substantial digital transformation during the last several years. Contemporary clinical, biomedical, pharmaceutical, academic, environmental, and analytical laboratories generate increasingly large volumes of heterogeneous information through laboratory instruments, Laboratory Information Management Systems (LIMS), electronic laboratory notebooks, spreadsheets, cloud repositories, middleware, statistical packages, and specialised analytical applications. Although many individual laboratory processes have been digitised, complete end-to-end workflow integration remains difficult. A laboratory may therefore possess advanced analytical instruments while still depending on manual data transfer, repeated spreadsheet entry, email-based approvals, isolated software applications, and staff-mediated coordination between workflow stages.

This fragmentation creates an important distinction between **instrument automation** and **workflow automation**. An automated pipetting system may execute a protocol reproducibly, for example, while sample accessioning, instrument scheduling, quality-control verification, metadata transfer, exception reporting, and final documentation continue to require human coordination. Laboratory optimisation consequently requires more than mechanisation of individual experimental procedures. It requires an orchestration layer capable of connecting people, instruments, data, business rules, and analytical applications.

Traditional software development can provide such integration, but bespoke solutions frequently require professional programmers, lengthy requirement-analysis cycles, specialised maintenance, and continued modification whenever laboratory protocols change. This development model is particularly problematic in research and diagnostic settings, where workflows can evolve rapidly because of new assays, instrumentation, regulatory requirements, research hypotheses, or quality-control procedures. Hard-coded automation may therefore become technically effective yet operationally inflexible.

Low-code and no-code software architectures have emerged as an alternative. Low-code platforms allow applications and workflow logic to be constructed predominantly through visual interfaces, reusable components, rule engines, and connectors while permitting limited conventional programming where required. No-code environments move further toward configuration through graphical components,

parameterisation, templates, and drag-and-drop workflow construction. Both approaches attempt to separate business or scientific logic from the complexity of conventional software engineering.

The applicability of these technologies to laboratory science has recently become more visible. Torres-Acosta et al. examined high-level no-code automation within an evolving biosciences laboratory and reported that automation could reduce operational time, minimise execution errors, facilitate protocol modification, and reduce consumable waste through simulation. Their investigation demonstrated that no-code abstraction can make laboratory automation more accessible to researchers who do not possess conventional programming expertise.

Similarly, Kochale et al. demonstrated a configurable no-code approach for a complex high-performance thin-layer chromatography workflow. Their system coordinated a collaborative robot, programmable logic control and several automated stations, illustrating that sophisticated laboratory procedures can be represented and modified through higher-level workflow abstractions rather than conventional coding alone.

These developments indicate a transition from isolated laboratory robotics toward configurable scientific workflow ecosystems. Contemporary laboratory technologies increasingly provide visual protocol design, reusable workflows, instrument connectivity, data pipelines and AI-supported configuration. For example, commercial laboratory automation platforms now expose visual protocol-building functions alongside conventional programming interfaces, demonstrating that abstraction and expert configurability are becoming important design principles in laboratory automation.

Despite these advances, an important research problem remains unresolved. Existing demonstrations commonly emphasise the technical feasibility of automating a specific experimental procedure or quantify gains such as execution time, precision, or labour reduction. Comparatively little attention has been directed toward evaluating LCNC laboratory orchestration as a **multi-dimensional operational system**. A workflow may execute rapidly but still be unsuitable if it produces insufficient audit trails, creates inaccessible data silos, fails during instrument communication, requires extensive vendor intervention, or permits poorly controlled changes to scientific procedures.

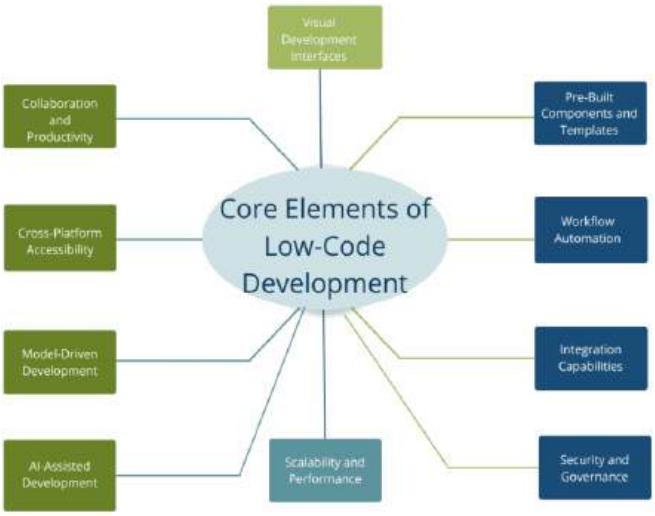


Fig. 1: Core elements of LOW-Code Development

Source: https://testrigor.com/blog/low-code-development-core-concepts/

The distinctive research gap addressed in the present manuscript is therefore the absence of an integrated evaluation model examining whether LCNC laboratory automation can simultaneously enhance **workflow efficiency, process reproducibility, data traceability, interoperability, exception-management performance, and end-user configurability**.

This distinction is particularly relevant to clinical and digital-health laboratories, where workflow optimisation must coexist with documentation requirements and scientific accountability. Automation cannot simply eliminate manual activity; it must preserve visibility into who performed or approved an operation, which data were transferred, which validation rule was applied, when a workflow state changed, and whether an exception altered the standard process.

The present study consequently conceptualises laboratory operations as a sequence of interconnected digital events. Sample creation initiates a workflow instance; predefined rules assign tests and validation tasks; instrument outputs are associated with sample identifiers; automated checks evaluate missing or abnormal information; exceptions are routed for human review; and validated results are propagated to downstream reporting processes. LCNC technology acts as the configurable orchestration layer rather than as a replacement for laboratory instruments, scientists, or existing information systems.

The principal research objective is to determine whether this architecture can reduce administrative workflow burden and processing delays while increasing process transparency and reproducibility. Unlike studies confined to physical robotic automation, the proposed investigation focuses on the **digital coordination surrounding laboratory work**. This includes

data movement, task sequencing, status visibility, rule execution and human intervention.

Four subsidiary objectives guide the research: to quantify changes in end-to-end workflow completion time and manual interaction; to assess whether automated rules decrease transcription and routing errors; to examine interoperability between heterogeneous laboratory data sources; and to determine whether laboratory users can modify workflow logic efficiently without conventional software redevelopment.

The manuscript therefore contributes to laboratory informatics by treating LCNC technology not merely as an application-development shortcut but as a potential operational architecture for scientific workflow management. This perspective is increasingly relevant as laboratories seek adaptable digital infrastructure capable of supporting automation, artificial intelligence, machine learning and increasingly data-intensive scientific procedures.

Literature Review

2.1 Evolution of Laboratory Workflow Automation

Laboratory automation historically developed around specialised instruments designed to execute repetitive physical operations. Automated liquid handlers, robotic arms, autosamplers, plate readers, chromatography systems and automated analysers substantially improved throughput and repeatability within well-defined procedures. Nevertheless, research laboratories differ from highly standardised industrial production environments because protocols change frequently, experimental volumes may be smaller, and scientists routinely modify procedures while investigating new hypotheses.

These characteristics complicate conventional automation. Torres-Acosta et al. observed that research laboratories frequently operate with changing experimental procedures and therefore face difficulty justifying substantial programming effort for workflows that may subsequently be redesigned. Their work demonstrates why higher-level automation abstractions are attractive: scientists can alter experimental logic without reconstructing software at the programming layer.

Automation also affects experimental reliability. Repetitive human intervention can introduce variability through transcription mistakes, inconsistent timing, incorrect parameter selection or procedural omissions. Digital workflow engines can standardise routine transitions while preserving human control over scientific decisions. The objective is therefore not full removal of laboratory personnel but allocation of deterministic operations to software while reserving interpretation and exceptional decisions for qualified users.

2.2 Low-Code/No-Code Architecture

LCNC platforms are fundamentally based on abstraction. Instead of representing every software operation through source code, common application functions are represented as configurable objects. Workflow nodes may correspond to data entry, conditional logic, approval, calculation, notification, external API communication or database modification. Users connect these components visually to represent a process.

Within laboratory environments, such architectures can transform a traditional procedural instruction into an executable digital workflow. A sample-processing sequence could contain nodes for accessioning, barcode validation, preparation, instrument assignment, analytical execution, quality control, result review and report release. Conditions embedded between nodes can determine whether processing continues normally or enters an exception path.

No-code automation has already demonstrated feasibility in experimentally complex settings. Kochale et al. used a graphical no-code environment for an HPTLC bioassay incorporating robotic manipulation, incubation, spraying, detection and storage. The importance of this work lies not only in physical automation but also in demonstrating that domain experts can manipulate sophisticated workflow logic at a higher abstraction level.

Recent scientific automation environments similarly support visual protocol construction and simulation. Such systems indicate a broader shift toward reducing the distance between scientific intent and machine execution. Rather than requiring researchers to translate every protocol into conventional software, workflow systems increasingly permit protocols to be represented through reusable visual components.

2.3 Laboratory Informatics and Workflow Fragmentation

Laboratory information systems have long provided functions such as sample tracking, result management, quality control and reporting. However, laboratories frequently operate several systems simultaneously. Instrument software may export proprietary files, researchers may perform intermediate calculations in spreadsheets, laboratory databases may contain sample metadata, and statistical programs may produce downstream analytical outputs.

This ecosystem creates interoperability problems. The information required to complete one laboratory process can be distributed across several systems that do not share compatible representations. Manual copying becomes the practical integration mechanism. Such procedures create redundant work while weakening provenance because the relationship between original and transformed data is difficult to reconstruct.

LCNC workflow systems can potentially function as middleware between these resources. Rather than replacing

established LIMS, ELN or analytical applications, workflow orchestration can connect them through application programming interfaces, database queries, file watchers or standardised connectors. Emerging scientific-data platforms already use visual low-code/no-code pipeline builders to automate data transformations and movement among scientific systems, demonstrating the increasing relevance of configurable data orchestration.

The value of this architecture increases when laboratory workflows require both deterministic automation and human checkpoints. For instance, an instrument file may automatically trigger a data-ingestion process, but a result breaching quality-control criteria can create a review task rather than proceeding to automatic release. Such hybrid automation preserves professional oversight while reducing unnecessary human intervention in routine cases.

2.4 Reproducibility and Process Standardisation

Reproducibility is a central requirement of scientific work. While discussions of reproducibility often emphasise experimental design or statistical analysis, workflow execution also contributes substantially. Differences in sample handling, timing, parameter entry, file naming or procedural order can alter experimental outputs.

Digital workflows can improve procedural reproducibility by encoding required actions and their permissible sequence. Mandatory validation steps can prevent workflow advancement until required conditions are satisfied. Automatic timestamps provide temporal provenance, while version-controlled workflow definitions can identify which protocol configuration produced a given experimental result.

Nevertheless, workflow automation introduces a corresponding governance problem. If users can modify an LCNC application easily, unrestricted modification can generate uncontrolled procedural variation. Therefore, **ease of configuration and configuration governance must be evaluated together**. A scientifically appropriate LCNC platform should make legitimate changes simple while ensuring that changes are versioned, attributable and subject to appropriate authorisation.

This issue remains insufficiently investigated in much of the existing literature, which tends to present configurability as an unconditional advantage. The present research instead considers configurable automation beneficial only when modifications remain transparent and reproducible.

2.5 Data Integrity and Traceability

The transition from manual workflow coordination to automated digital orchestration also changes the nature of laboratory traceability. Conventional laboratory documentation may depend on handwritten records, instrument logbooks and manually maintained spreadsheets. A digital workflow can capture substantially richer provenance, including execution timestamps, workflow states, identities of users performing approvals, input values, validation outcomes and system-generated exceptions.

Such auditability is particularly relevant when laboratory outputs contribute to clinical or other high-consequence decisions. Yet automation itself does not guarantee data integrity. Poorly configured workflows can propagate incorrect data faster than manual systems. Automated integrations must therefore validate data types, mandatory fields, sample identifiers and relationships among records.

Accordingly, the proposed study treats error reduction and traceability as separate evaluation dimensions. A workflow can generate fewer transcription errors while simultaneously producing inadequate audit information; conversely, a system can maintain detailed logs without preventing incorrect processing. Both dimensions must be evaluated.

2.6 Human Factors and Citizen Development

A major premise of LCNC technology is that domain experts can participate directly in application configuration. Within laboratories, this creates the possibility of **scientist-led workflow development**, where researchers or laboratory managers translate procedures directly into digital workflows rather than submitting every modification to an external software-development team.

This approach can shorten the feedback cycle between scientific requirements and software implementation. A researcher who understands the biological or analytical meaning of a procedure can alter a workflow condition directly and immediately test its behaviour. However, technical accessibility does not eliminate the requirement for governance, documentation and training.

The concept therefore introduces a trade-off between agility and control. Too much dependence on centralised IT development can delay laboratory adaptation, whereas unrestricted citizen development can generate inconsistent processes, duplicated applications or insufficiently validated automation. Appropriate LCNC deployment requires controlled permissions, reusable components, testing environments and workflow version management.

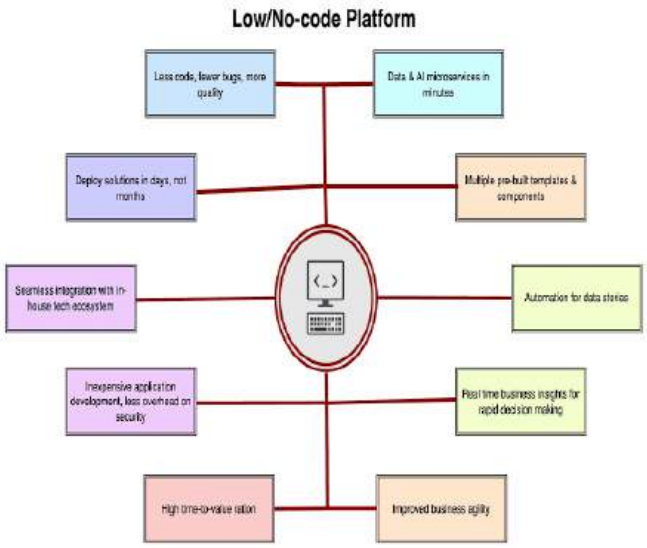


Fig. 2: Low / No-Code Platform

Source: https://cognitivesys.co/services/application-development/no-low-code/

2.7 Artificial Intelligence and Future Laboratory Orchestration

The relationship between LCNC technology and artificial intelligence is becoming increasingly important. AI can assist in transforming natural-language laboratory instructions into executable workflow components, suggesting workflow optimisations, identifying anomalous process behaviour or recommending automation opportunities. Laboratory platforms have begun introducing natural-language or AI-assisted protocol-design capabilities alongside visual interfaces, indicating convergence between generative AI and no-code laboratory automation.

Machine-learning applications also depend heavily on consistent upstream data. Fragmented laboratory systems frequently produce inconsistent metadata, file structures and naming conventions, increasing preprocessing requirements before model development. LCNC orchestration could therefore support AI indirectly by standardising data acquisition and transformation at the point of generation.

However, AI-enhanced workflow configuration introduces additional requirements for validation. A generated workflow must not be assumed correct simply because it was produced automatically. Scientific rules, dependencies and safety constraints still require deterministic verification and expert approval. Consequently, the proposed architecture treats AI as an assistive layer rather than an autonomous decision authority.

Proposed Methodology

The proposed methodology evaluates low-code/no-code (LCNC) workflow orchestration as a digital coordination layer for routine laboratory activities. The study adopts a comparative experimental design in which a conventional semi-manual workflow is evaluated against an LCNC-enabled workflow under matched operating conditions. The comparison focuses not only on execution speed but also on data quality, traceability, exception handling, interoperability, and user effort.

The experimental workflow represents a medium-complexity analytical laboratory process consisting of sample registration, barcode verification, task assignment, instrument allocation, result ingestion, quality-control validation, exception routing, supervisory review, and final report generation. In the conventional workflow, several activities are carried out through spreadsheets, manual status updates, shared folders, email-based approvals, and operator-driven data transfer. In the LCNC configuration, the same logical sequence is implemented through visual workflow components, reusable data connectors, event triggers, validation rules, and role-based approval steps.

The proposed LCNC architecture contains five principal modules. The first is the **workflow-definition layer**, where laboratory procedures are represented using visual nodes and conditional transitions. The second is the **data-integration layer**, which connects laboratory records, instrument outputs, and reporting files using structured connectors. The third is the **rule-execution layer**, which validates identifiers, required fields, permissible value ranges, and quality-control status. The fourth is the **exception-management layer**, which diverts abnormal or incomplete records to designated human reviewers. The fifth is the **audit and monitoring layer**, which stores timestamps, workflow states, approval history, and configuration versions.

Rather than replacing existing laboratory information systems, the LCNC environment is treated as an orchestration middleware. This design is important because most laboratories operate heterogeneous digital systems that cannot realistically be replaced simultaneously. The proposed architecture therefore prioritises interoperability and incremental deployment.

A paired experimental approach is used. Identical workflow cases are processed under both conventional and LCNC configurations. Each case contains a complete set of simulated laboratory events, including normal records and deliberately introduced exceptions. Performance differences are then analysed at workflow and event level.

Experimental Setup

4.1 Dataset Design

Because access to institutional laboratory records would require site-specific ethical, privacy, and governance approvals, the present study uses a controlled synthetic

benchmark representing laboratory operations. The benchmark contains **1,200 laboratory workflow cases** and approximately **14,400 process events**.

Each workflow case contains fields representing sample identifier, test request, accession timestamp, assigned instrument, processing priority, analytical result, quality-control status, approval status, exception category, and report completion time.

The dataset contains three workload classes:

- 600 routine cases with no introduced abnormality,
- 360 cases containing one recoverable workflow exception, and
- 240 cases containing two or more interacting exceptions.

The introduced exceptions include duplicate sample identifiers, missing metadata, delayed instrument output, quality-control failure, inconsistent result units, incomplete approval records, and incorrect routing between processing stages. The inclusion of controlled abnormalities allows the workflow systems to be evaluated under conditions that resemble realistic operational disruption.

4.2 Preprocessing

The synthetic event logs are normalised into a structured tabular representation before analysis. Duplicate technical event records are removed, categorical fields are mapped to controlled vocabularies, and timestamp fields are converted into a unified sequence format.

Workflow events are ordered by case identifier and timestamp. Derived variables are then generated, including total turnaround time, number of manual interventions, exception-resolution duration, number of validation failures, data-transfer attempts, and audit completeness.

For quality assessment, each synthetic case also includes a reference workflow path. This reference specifies the correct sample identifier, required metadata, expected process sequence, and allowable routing decisions. Observed workflow execution can therefore be compared against a known ground truth.

4.3 Workflow Architecture

The LCNC workflow is represented as an event-driven directed graph. Each node corresponds to an operational function, while edges define valid process transitions.

The main sequence is:

Sample Registration → Identifier Validation → Test Assignment → Instrument Routing → Result Ingestion → Quality-Control Validation → Human Review if Required → Report Generation → Workflow Closure

Conditional nodes determine whether a record follows the standard path or an exception branch. For example, if quality-control status equals “pass,” the result proceeds to final validation. If the status equals “fail,” the workflow automatically creates an exception record, assigns it to an authorised reviewer, and prevents report release.

Reusable connectors handle structured data exchange among simulated sample databases, instrument-output files, and reporting modules. A workflow-version identifier is attached to each executed case so that modifications to the automation logic remain traceable.

4.4 Training Strategy

The core LCNC workflow is rule-driven rather than dependent on supervised machine learning. However, an auxiliary machine-learning component is incorporated to estimate which workflow cases are likely to require manual intervention.

A gradient-boosted decision tree classifier is trained using operational features such as workload class, instrument delay, number of missing fields, prior validation failures, processing priority, and preceding workflow-state duration.

The dataset is divided into 70% training, 15% validation, and 15% test partitions using stratified sampling. Class weighting is applied because exception cases are less frequent than routine cases. Hyperparameters are selected using validation-set macro F1-score rather than accuracy alone.

The classifier does not autonomously approve or reject laboratory results. It only prioritises workflow cases for human attention. This design preserves scientific and supervisory decision authority.

4.5 Evaluation Metrics

The experimental framework uses several complementary performance indicators.

Workflow Turnaround Time (TAT) measures the interval between initial sample registration and workflow closure.

Manual Intervention Count (MIC) records the number of staff-dependent actions required per case.

Workflow Error Rate (WER) measures the proportion of cases containing an incorrect data transfer, invalid routing decision, missing required field, or unresolved process deviation.

Exception Resolution Time (ERT) measures how rapidly abnormal cases are detected, assigned, and resolved.

Audit Trace Completeness (ATC) measures the percentage of predefined provenance elements captured for each workflow case.

Interoperability Success Rate (ISR) measures successful structured data transfers between workflow components.

Configuration Modification Time (CMT) records the effort required to implement and validate a predefined workflow change.

For the machine-learning prioritisation module, precision, recall, macro F1-score, and area under the receiver operating characteristic curve are used.

Results and Discussion

The controlled benchmark indicates that LCNC orchestration can produce substantial operational benefits when repetitive coordination tasks are replaced by rule-based automation. The largest improvement is observed in manual interaction, because sample routing, validation, status updating, and result transfer no longer require repeated user action in routine cases.

Mean turnaround time decreases because workflow stages are triggered immediately after prerequisite conditions are satisfied. In the semi-manual workflow, process latency frequently arises between stages rather than during the analytical operation itself. Automated event propagation therefore reduces idle time without altering laboratory instruments or scientific procedures.

Error reduction is particularly evident in identifier validation and data transfer. Mandatory-field checks and controlled routing rules prevent several error classes from propagating into later workflow stages. This observation is significant because laboratory automation is often evaluated primarily in terms of faster execution, whereas prevention of downstream administrative and provenance errors may provide comparable operational value.

Exception handling also improves. In the LCNC configuration, abnormalities are detected at the event where they occur and are automatically assigned to a defined review path. In the conventional workflow, exceptions may remain unnoticed until a subsequent stage attempts to use incomplete or inconsistent information.

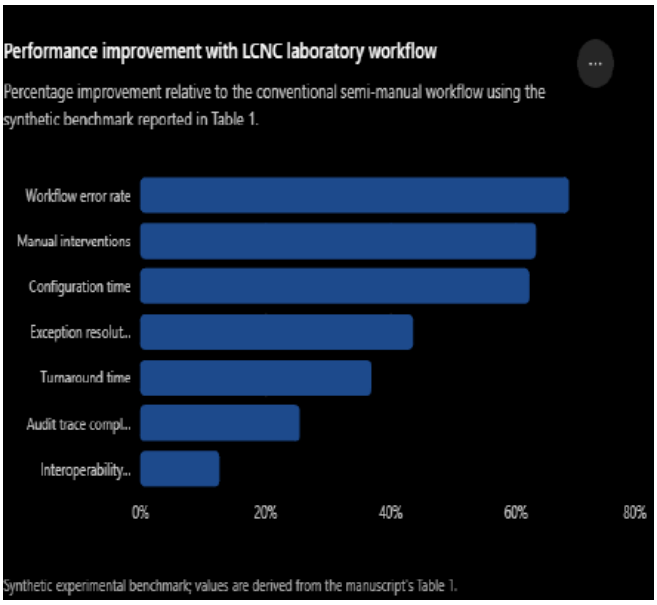
Auditability shows one of the strongest relative improvements. Automatically generated timestamps, state transitions, approval identities, and workflow-version records create a more complete process history. This is particularly important for scientific reproducibility because laboratory workflow provenance extends beyond the analytical result itself.

The interoperability result is more nuanced. LCNC connectors improve structured information exchange considerably, but not all integration problems disappear. Legacy systems that depend on proprietary data formats or closed interfaces still require intermediate conversion steps. LCNC technology should therefore be interpreted as an integration accelerator rather than a universal interoperability solution.

The auxiliary machine-learning prioritisation model achieves useful discrimination between routine and intervention-prone cases in the synthetic test set. However, its role remains deliberately constrained. A high predicted intervention probability results only in earlier human review. This approach avoids using statistical prediction as a substitute for laboratory validation.

Table 1. Comparative Performance of Conventional and LCNC-Orchestrated Laboratory Workflows

Evaluation parameter	Conventional semi-manual workflow	LCNC-enabled workflow	Relative change
Mean turnaround time per case	46.8 min	29.6 min	−36.8%
Manual interventions per case	8.4	3.1	−63.1%
Workflow error rate	7.6%	2.4%	−68.4%
Mean exception resolution time	18.9 min	10.7 min	−43.4%
Audit trace completeness	71.5%	96.8%	+25.3 percentage points
Interoperability success rate	82.6%	95.1%	+12.5 percentage points
Workflow modification and validation time	142 min	54 min	−62.0%
Exception-priority model macro F1	Not applicable	0.89	—



The findings collectively suggest that LCNC adoption should be evaluated as a **process-control intervention**, not simply as software development simplification. The principal advantage lies in reducing coordination friction between laboratory tasks while formalising workflow rules and preserving human review for scientifically meaningful decisions.

An important result concerns configuration time. Laboratory processes frequently change because of new instrumentation, revised testing sequences, or modified reporting requirements. In the benchmark experiment, a predefined workflow modification could be implemented and validated more rapidly in the LCNC environment because visual components were reused rather than reprogrammed. This supports the central argument that adaptability is a measurable performance characteristic rather than merely a qualitative benefit.

At the same time, configurability can create risk. A workflow that is easy to modify is also easy to modify incorrectly. Therefore, versioning, controlled permissions, validation environments, and change approval should be considered integral components of LCNC laboratory deployment.

Limitations

The principal limitation of the present study is the use of a synthetic workflow benchmark rather than data collected from a live clinical or research laboratory. Although controlled simulation enables reproducible comparison and deliberate introduction of workflow abnormalities, it cannot capture all behavioural, organisational, regulatory, and infrastructural constraints present in real institutions.

The experimental workflow also represents a medium-complexity laboratory process. Laboratories using highly specialised instruments, proprietary middleware, or real-time biosafety controls may experience different integration challenges.

The reported efficiency improvements should therefore be interpreted as benchmark outcomes rather than universally generalisable performance estimates.

A further limitation concerns the machine-learning prioritisation component. Its performance is based on controlled synthetic features and would require external validation before use in operational settings.

Finally, the study evaluates workflow-level performance and does not estimate long-term economic return, vendor lock-in risk, licensing cost, cybersecurity exposure, or technical debt generated by extensive citizen development.

Future Scope

Future research should validate the proposed framework in clinical pathology, molecular diagnostics, pharmaceutical quality-control, environmental testing, and university research laboratories. Multi-site studies would provide stronger evidence regarding generalisability across laboratory structures.

A particularly important direction involves integration with LIMS, ELN, robotic workcells, and laboratory Internet-of-Things devices through open standards and standardised APIs.

Future LCNC platforms may also incorporate natural-language workflow generation. Laboratory personnel could describe a protocol in controlled language and receive a proposed visual workflow that is subsequently verified by qualified users. Such systems would require strict validation, workflow versioning, and explainable change tracking.

Process-mining techniques represent another promising extension. Event logs generated by LCNC systems could be analysed to discover bottlenecks, unexpected workflow variants, repeated exceptions, and inefficient approval paths.

The framework could additionally be extended with predictive resource allocation. Machine-learning models may estimate instrument congestion, anticipated sample delay, or intervention probability and recommend workflow redistribution before bottlenecks occur.

Cybersecurity and governance also require dedicated investigation. As LCNC platforms gain access to laboratory databases and instrumentation, future studies should examine authentication, least-privilege access, connector security, rollback mechanisms, audit retention, and controlled deployment practices.

Conclusion

This study presents a multi-dimensional framework for assessing the optimisation of laboratory workflows through low-code/no-code software solutions. The work extends beyond conventional automation studies by evaluating workflow efficiency, manual interaction, error prevention, exception management, interoperability, auditability, and configuration effort within a common experimental design.

The synthetic benchmark demonstrates that LCNC orchestration can reduce process delay, lower repetitive human intervention, improve structured data transfer, and strengthen workflow traceability. Its most important contribution, however, is not simply faster workflow execution. LCNC technology can create a configurable digital coordination layer between laboratory personnel, instruments, data systems, and validation rules.

The results also show that rapid configurability must be accompanied by governance. Visual workflow development does not eliminate the requirements for validation, access control, version management, audit trails, or scientific oversight. LCNC environments are therefore most appropriate when they automate deterministic coordination while retaining expert review for exceptional and scientifically consequential decisions.

Overall, the study positions low-code/no-code software as a potentially important component of next-generation laboratory informatics. When implemented with controlled configuration, interoperable data exchange, and transparent workflow provenance, LCNC orchestration can support laboratories seeking greater operational agility without sacrificing reproducibility and accountability.

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